CHAPTER 5

IS SOCIO-ECONOMIC STATUS A MAIN DETERMINANT OF EDUCATIONAL OUTCOMES?

The one strong relationship revealed or assumed by Education Production Function Research – see Section 5 in Chapter 1 – is that between Educational Outcomes and Socio-Economic Status, which are strongly positively correlated. If MERA was a success in providing a higher basic level of education, and if this led to better outcomes in poorer school districts, then the correlation between Socio-Economic Status and Educational Outcomes should have weakened over time as the reforms took effect.

Correlation between multiple input variables and multiple output variables is measured in this chapter using average efficiency scores from the CCR model with proxies for Socio-Economic Status as inputs and Test Scores as outputs. Strong correlation between Socio-Economic Status and Test Scores is shown to exist. If a trend can be identified from the results it is a strengthening of the relationship rather than a weakening of the relationship, which implies that MERA has not been successful.

5.1 Measuring Correlation Using The CCR Model

Statistical Correlation is measured on a scale ranging from 1 to minus 1. An average efficiency score of zero or less cannot be derived from the CCR model since at least one DMU will be 100 per cent efficient and negative efficiency scores do not arise as a ratio of positively priced positive values. The approach, referred to as the "sorting strategy", is to establish a scale for each set of data by sorting the data in two ways.

1. All the inputs and all the outputs are sorted into the ascending order.

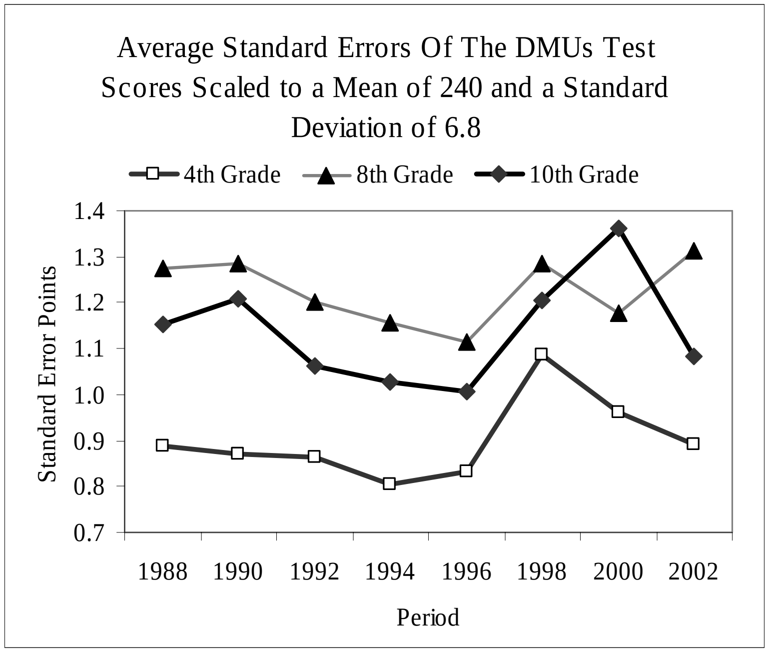
2. All the inputs are sorted into ascending order and all the outputs into descending order.

The first sorting gives a set of data that is highly positively correlated, while the second sorting gives a set of data that is highly negatively correlated. Average efficiency scores from the CCR model applied to the two sets of data render a range of average efficiency scores between highly positively correlated and highly negatively correlated. Using the actual data values means that the distributions of the parameters (SES Proxies and Test Scores) remain constant between the calculations of efficiency for the highly positively correlated, the highly negatively correlated and the actual unsorted data. The sorting strategy also controls for the number of parameters used on either side: inputs or outputs. In other words Factors 3 through 8 from Section 8 in Chapter 4 are kept constant.

This leaves Factors 1 and 2. Factor 1 is precisely the effect that is to be measured – correlation. Test scores for 4 disciplines for 180 DMUs have relationships that can be vertical – Math Scores have a normal distribution with a mean of x and a standard deviation of y, so an individual math score can be described by the distribution and the z-score – or the relationship can be horizontal, among the Math, Reading, Science and History scores for a particular DMU. If a school is a "good" school the expectation is that the scores in all disciplines will be high, if a "bad" school then the expectation is that the scores in all disciplines will be low. There should be little statistical independence among the scores for the different disciplines. Sorting a column (or sorting vertically) does not change the distribution or the z-score of any of the values in the column, but it does upset the horizontal relationships. If the effect of sorting is to increase the degree of statistical independence then average efficiencies from the CCR model may increase. Conversely if the degree of statistical independence decreases the CCR model may give higher average efficiency scores for the sorted than for the actual data because there is less scope for a DMU to use pricing to achieve higher efficiency scores in the sorted data – see Examples One, Two and Three in Section 5 of Chapter 4. So highly correlated data, which has some degree of statistical independence can result in efficiency scores that are higher than those obtained from sorting the same data into ascending order by inputs and outputs.

Unfortunately, although the effect of statistical independence between the parameters should be taken into account, it is not quantifiable. Measuring the statistical independence among the test scores using the average of the standard deviations of the test scores for each school district divided by the square root of the number of disciplines tested (the average of the standard errors) revealed very small standard errors and very little variability in these standard errors over time – see Figure 5.01. Thus although the inability to quantify the effect of, or control for, the degree of statistical independence makes analysis of trends over time imprecise there are reasons to think that the effect is limited.

Figure 5.01 – Average Standard Errors of The DMUs' Test Scores.

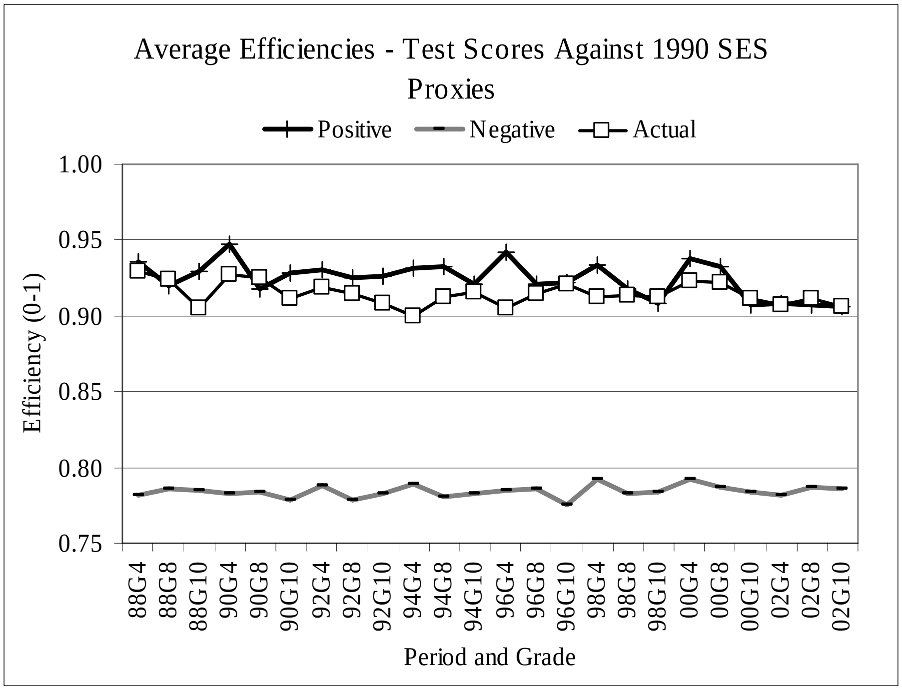


In summary, the approach to the estimation of correlation used in this chapter is to hold six of the eight factors constant across eight time periods, and to use the sorting strategy to identify ranges of efficiency scores that represent high positive correlation and high negative correlation. Comparing the efficiency scores derived from the actual data with these ranges allows the strength and direction of correlation to be estimated.

5.2 SES and Education Outcomes Are Highly Correlated

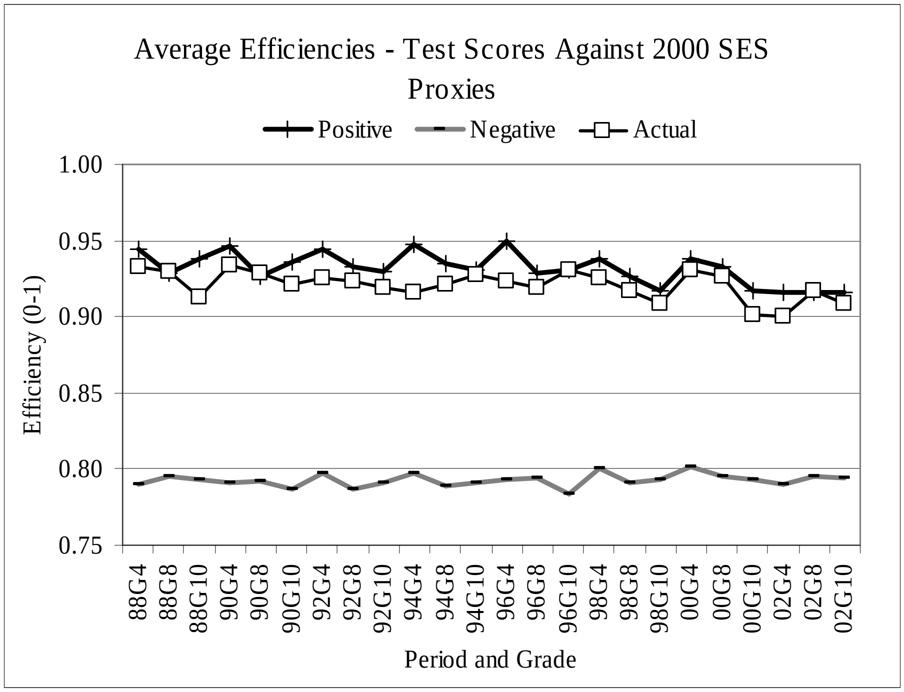
The proxies for Socio-Economic Status used were: Education, Median Income, TSEI2 and Poverty. Two sets of proxies were calculated: one from 1990 census data and the other from 2000 census data. Test scores came from 4^{th}, 8^{th} and 10^{th} grade tests in 1988, 1990, 1992, 1994, 1996, 1998, 2000 and 2002. 24 models were run covering three grades and eight time periods. Models were also run using 1990 SES proxies for all periods and using 2000 SES Proxies for all periods.

Figure 5.02 – All Average Efficiency Scores – Test Scores Against 1990 SES Proxies.



The results from models using 1990 SES proxies are plotted as Figure 5.02. The Figure shows clearly that the average efficiencies from the models using the actual data, are significantly closer to the average efficiencies from the models using the actual data sorted in such a way as to create Positive Correlation, than they are to the average efficiencies from the models using actual data, sorted in such a way as to create Negative Correlation. Figure 5.03 shows the average efficiencies based on 2000 SES proxies. Again, as might be expected, actual data average efficiencies are very much nearer to the Positive data average efficiencies than to the Negative data average efficiencies.

Figure 5.03 – All Average Efficiency Scores – Test Scores Against 2000 SES Proxies.



These results strongly support the proposition that Socio-Economic Status was highly correlated with Educational Outcomes in Massachusetts between 1988 and 2002.

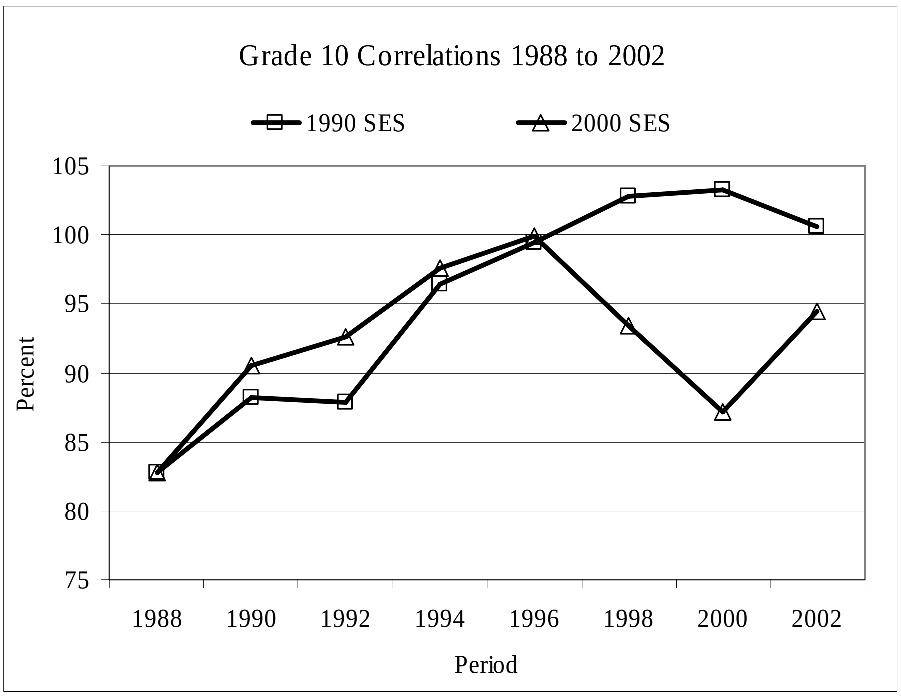
5.3 Change Over Time in The Relationship Between SES and Test Scores

If MERA was successful in reducing inequity in funding and if greater equity in turn was reflected by improvement in the educational outcomes in districts with lower Socio-Economic Status measures, then greater equity should results in a loosening of the correlation between Socio-Economic Status and Educational Test Scores.

When the range between the average efficiency derived from the actual data sorted to be Positively Correlated and the average efficiency derived from the actual data is divided by the range between the average efficiency derived from the actual data sorted to be Negatively Correlated and the average efficiency derived from the actual data, this yields a percentage between 0 and 100 percent – and sometimes higher as a consequence of the impacts of sorting on Factor 2, discussed in Section 1 of this Chapter. Values around zero imply very high negative correlation in the data and values around 100 imply very high positive correlation in the data.

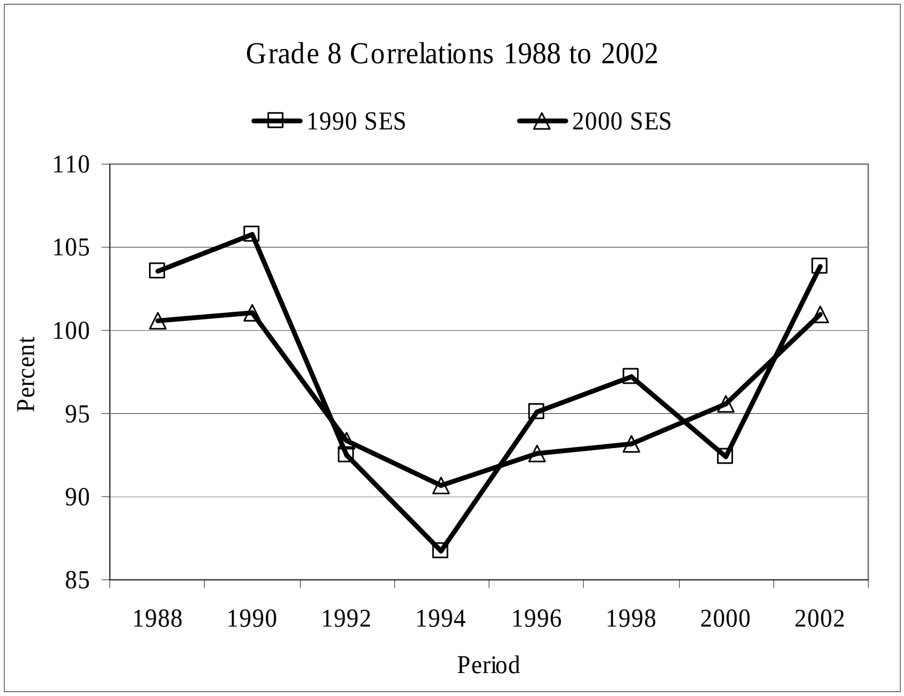
For efficiencies based on Grade 10 tests scores there is a clear trend towards greater correlation between SES and test scores over time – see Figure 5.04, which shows the results using both 1990 SES proxies as inputs and 2000 SES proxies as inputs.

Figure 5.04 – Trend in "Correlations" Between 1990 and 2000 SES Proxies and Grade Test Scores.



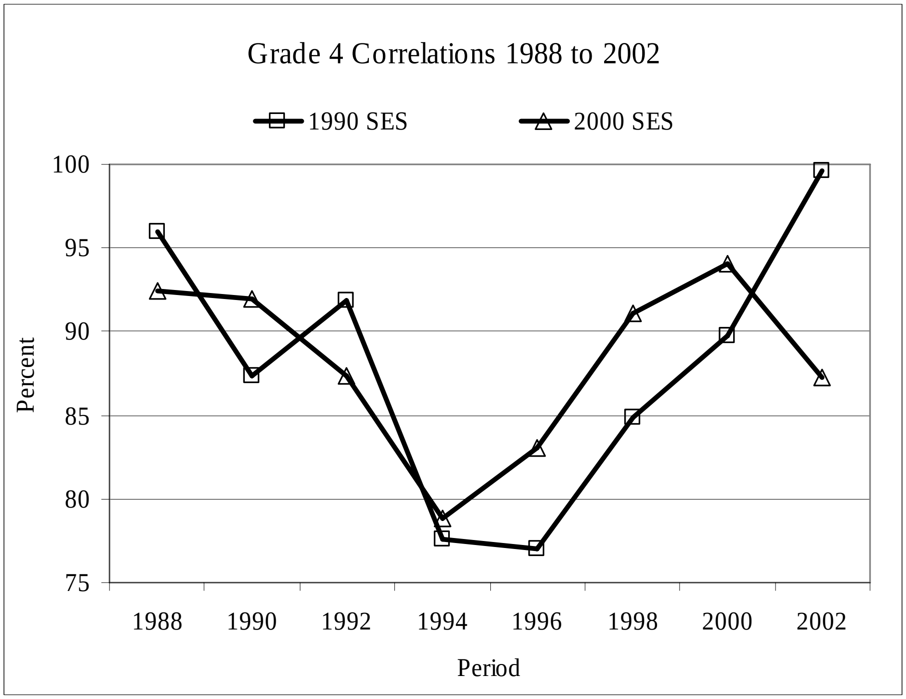
For efficiencies based on Grade 8 tests scores the picture is more ambiguous – see Figure 5.05. Both 1990 and 2000 SES proxy based "Correlations" suggest increasingly stronger positive correlation between test scores and SES after 1994, when MERA came into effect.

Figure 5.05 – Trend in “Correlations” Between 1990 and 2000 SES Proxies and Grade 8 Test Scores.



For efficiencies based on Grade 4 tests scores the picture is also ambiguous – see Figure 5.06. Again correlation between SES and test scores appears to have become more positive between 1994 and 1998. Then based on the 2000 SES proxies, the relationship falls off some way toward levels seen in 1996.

Figure 5.06 – Trend in “Correlations” Between 1990 and 2000 SES Proxies and Grade 4 Test Scores.

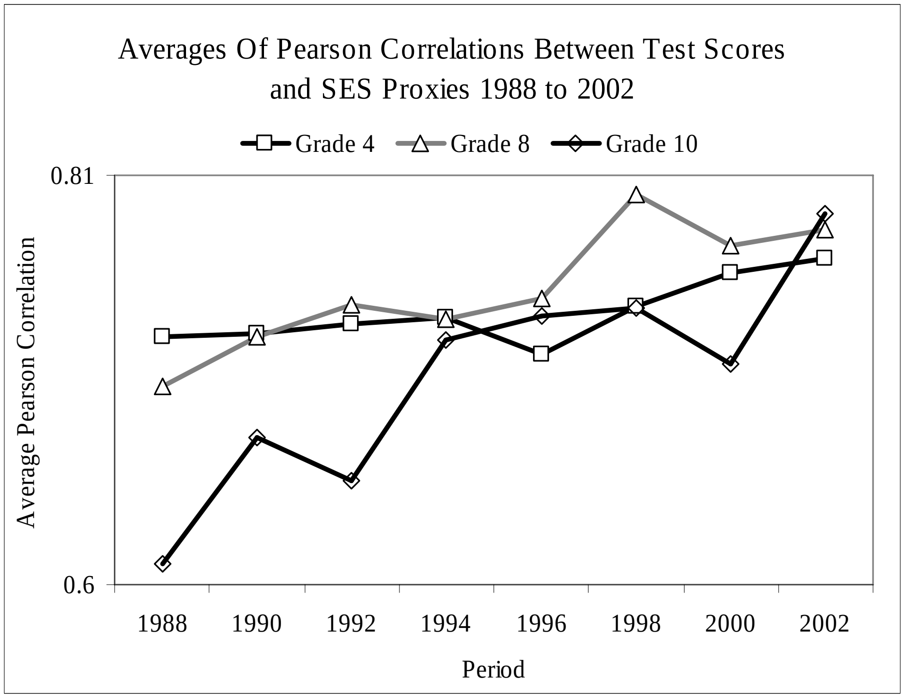


It is not possible to draw any categorical conclusions from this analysis. Looking at the period between 1994 and 2000 it would be possible to argue that, contrary to expectation, the relationship between SES and Educational Outcomes strengthened with the implementation of MERA. The Grade 10 results seem to show this as a fairly consistent trend since1988. The results for Grades 4 and 8 cast some doubt on this interpretation. In particular the sensitivity of the Grade 8 results to the scaling of the test scores calls the whole process into question.

5.4 Averages of Pearson Correlations

The averages of Pearson Rank Correlations between each of the SES Proxies and each of the test scores were calculated for all periods and grades and the trends in these averages were plotted as Figure 5.07. The results seem to confirm the results of the average efficiencies from the CCR models in that there is a clear trend in Grade 10 towards a higher positive correlation between test scores and SES.

Figure 5.07 – Trend in Averages of Pearson Correlations Between SES Proxies and Test Scores.



The average Pearson Correlations based on Grade 8 and Grade 4 test scores also trend upwards although less steeply. All P-values were less than 0.000. This analysis lends support to the results in Section 3 of this Chapterand suggests that the CCR model is estimating correlation reasonably well in spite of the complication introduced by the inability to adjust for, or control for, Factor 2.

5.5 Conclusions

There is no doubt from the Pearson Correlations or from the CCR model average efficiency scores that there is a strong positive correlation between measures of Socio-Economic Status and Educational Outcomes in general.

On balance the trends in the strength of the positive correlation (Pearson or CCR model based) seem to be towards a strengthening rather than a weakening of the relationship between Socio-Economic Status and Educational outcomes in Massachusetts both before MERA and since MERA. This implies that MERA has not had the effect of making educational outcomes more equal.